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## **Report Title**

Evaluating the Contribution of Uncertainty Management to a Fusion System

### **ABSTRACT**

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## Evaluating the Contribution of Uncertainty Management to a Fusion System

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**Abstract—** *By its very nature, fusion requires managing uncertainty. While uncertainty management is built into many standard low-level fusion algorithms, and the importance of uncertainty management is widely recognized at all levels of the JDL hierarchy, there is less commonality of approaches to uncertainty management for high-level fusion. Evaluation of the contribution of uncertainty management to a fusion system is distinct from, although related to, evaluating the fusion system as a whole. The evaluation should consider the purpose for which fusion is being performed, and measure the contribution of uncertainty management to this purpose. The concept of expected value of sample information from decision theory provides a conceptual framework for thinking about the role of uncertainty management in fusion systems.*

**Keywords:** *Uncertainty Management; Expected Value of Sample Information; Evaluation.*

### I. EVALUATING UNCERTAINTY VS EVALUATING FUSION

Information fusion “combine[s] information from multiple sources... to achieve inferences that cannot be obtained from a single sensor or source, or whose quality exceeds that of an inference drawn from any single source.” [1, p. xiii] By the very nature of the fusion problem, an ability to cope with uncertainty is a fundamental requirement for a fusion system.

Uncertainty processing is built into standard low-level fusion algorithms. For example, error ellipses are a fundamental ingredient of data association and state updating algorithms for multitarget tracking systems. These systems take uncertainty as a given; fusion serves to reduce the uncertainty by combining reports in a way that accounts properly for their individual and joint uncertainty.

At Levels 2 and above in the JDL hierarchy, recognition of importance of uncertainty remains, but there is far less commonality in approaches both for reasoning with uncertainty and for evaluating the impact of these approaches on the fusion process. There is a bewildering variety of information sources and types of outputs for high-level fusion systems. Characterizing their associated uncertainties and assessing their impact is a daunting challenge. Furthermore, especially at higher JDL levels, we must consider not just uncertainty related to individual information sources and hypotheses, but also how uncertainty propagates through chains of indirect evidential support. In addition, it is often important to represent and reason with ancillary evidence, or evidence about the nature and force of an evidential relationship [2].

Evaluating the uncertainty management aspect of a fusion system is only one aspect, albeit important, of evaluating the fusion system as a whole [3]. How uncertainty management contributes to performance of the fusion system is the key issue addressed by the ISIF working group on evaluation of techniques for uncertainty representation (ETURWG). To that end, the ETURWG developed an ontology designed to capture the concepts relevant to evaluating uncertainty of information fusion systems [3]. The *Criteria* class of the URREF ontology captures key measures relevant to how a fusion system represents and reasons with uncertainty, and how uncertainty contributes to performance of the system as a whole.

### II. EVALUATION FOR PURPOSE

In examining the role of uncertainty, it is essential to keep in mind the purpose for which fusion is being performed. Generally, this is to provide the necessary information inputs to support some kind of decision. Effective information fusion reduces uncertainty, but uncertainty reduction comes at a cost. How much and what kind of uncertainty reduction is worth achieving depends on how the results will be used. As a simple example, suppose we are interested in the whereabouts of John, who is a suspect in an assassination that occurred on April 3. If the purpose is to provide an alibi, then “John was somewhere in France on April 3” is an accurate enough localization if the assassination occurred in New York, but not if it occurred in Paris. As another example, typing an object as a hostile military vehicle may be sufficient identification for targeting under some rules of engagement; while a more precise type identification and/or intent assessment may be necessary under different rules of engagement. These examples illustrate the principle that designing and evaluating the uncertainty management component of fusion systems requires understanding how the fused results will be used. Different design tradeoffs are appropriate for different end uses. Distinct metrics of output quality and different thresholds of a given metric may be appropriate for different purposes.

A basic premise of fusion is that combining noisy inputs from multiple sources, especially sources with uncorrelated errors, can give higher quality results than the individual inputs. A corollary is that reducing the uncertainty of individual inputs to a fusion system may have lower payoff than increasing the number of different kinds of inputs [4]. That is, fusing many cheap but inaccurate inputs often gives higher quality outputs than fusing fewer but more accurate inputs.

In a related vein, for some higher-level fusion problems, there may be diminishing returns from greater accuracy in inputs from low-level fusion systems. For example, a simulation study by Wright et al. [5] found that the fidelity of situation estimates was relatively insensitive to variations (within a reasonable range) in some kinds of low-level fusion error. In particular, platoons could be reliably identified despite a moderate probability of missed detections, false alarms and incorrect associations. It is important for system designers to understand how errors and imprecision in low-level fusion results contribute to errors and imprecision in results of direct interest to decision makers. Such understanding enables more informed design tradeoffs.

### III. MEASURING THE VALUE OF INFORMATION FUSION

The concept of Value of Information from decision theory provides a useful conceptual framework for evaluating the role played by uncertainty management in fusion systems. In decision theory, we model a decision situation as consisting of a set  $\{d: d \in D\}$  of *allowable options*, a set  $\{s: s \in S\}$  of *possible world states*, a *probability distribution*  $P(s|d)$  for the world state given each allowable option, and a *utility function*  $u(s)$  representing the value to the decision maker of each possible world state. We may decompose the world state  $s=(r,e,y)$  as a result  $r$  of direct interest, observable evidence  $e$ , and unobserved but aspects  $y$  of interest only insofar as they are relevant to the result. The utility  $u(s) = u(r)$  depends only on the result of direct interest.

The decision maker's optimal choice is to maximize expected utility. With no evidence, the expected utility is:

$$u^* = \max_d \{E_{p(s)}[u(r)]\}$$

where the expectation is taken with respect to the distribution  $p(s) = p(r,e,y)$ . Now, suppose evidence  $e$  (which in general may include multiple items of evidence from different sources) is processed by the fusion system, resulting in an updated probability distribution  $p(s|e)$  that incorporates the new information. The expected utility:

$$u^{**}(e) = \max_d \{E_{p(s|e)}[u(r)]\}$$

is a function of the evidence  $e$ . Prior to observing  $e$ , our expected gain in utility from the observation is the *expected value of sample information* [6]:

$$\text{EVSI} = E_{p(e)}[u^{**}(e) - u^*]$$

EVSI is always non-negative, and is positive when the information has the potential to improve the decision. Thus, EVSI provides "simple and elegant measure" (c.f. [7]) to evaluate the contribution of information fusion. Conceptually, we can use EVSI to compare two fusion systems according to their contribution to improving decision-making.

It may be extraordinarily difficult or even infeasible, both computationally and from a domain modeling perspective, to quantify EVSI explicitly. Nevertheless, the idea of EVSI can help to inform thinking about the value of a fusion system. Furthermore, there have been many advances recently in

tractable exact and approximate computation of value of information [7]. Evaluating fusion systems from the perspective of EVSI can capture aspects of the mission that cannot be captured from more traditional measures of information gain (e.g., [8]). Turning to a comparison of different methods of fusing information, decision theory provides a conceptual framework for measuring their relative contributions. Specifically, we can compare them according to the expected utility each system achieves.

### IV. PRACTICALITIES

For fusion systems of realistic complexity, computation of the value of fusion will typically be infeasible. However, it is useful to conceive of evaluation as an attempt to measure the contribution of an uncertainty management approach to the overall performance of the fusion system. We can develop metrics to evaluate different aspects of performance (as laid out in [3]) and consider how to measure these aspects in practice. Even when there is no agreement among stakeholders on how to combine the factors into a single overall utility function, considering the factors separately can give insight into the strengths and weaknesses of different approaches.

If the objective is to compare different uncertainty management methods, there is no substitute for direct comparison of performance on common data sets. Obtaining ground truth for high-level fusion problems is typically quite challenging. Comparison on simulated data sets may be the only option, and even that may be difficult. Still, if the community is to advance, it is necessary to develop a set of benchmark problems and data sets. A model might be the UC Irvine machine learning repository [9].

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